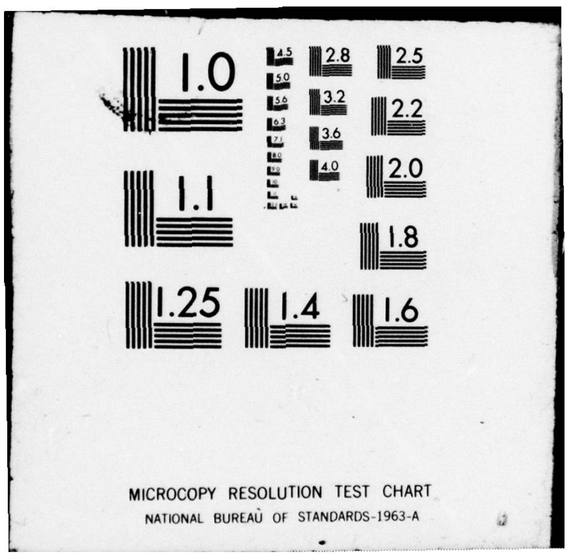
AD-A071 612 MICHIGAN UNIV ANN ARBOR HUMAN PERFORMANCE CENTER F/G 12/1
INTERSESSION VARIABILITY AND STRESS: A MONTE CARLO STUDY.(U)
JUN 79 E NOMA N00014-76-C-0648
UNCLASSIFIED 014523-6-T NL

1 OF 1
AD
A071612

END
DATE
FILMED
8-79
DDC


1.0
1.1
1.25
1.4
1.6
1.8
2.0
2.2
2.5
2.8
3.2
3.6
4.0
4.5
5.0
5.6
6.3
MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

(12) SC

(14) 014523-6-T, TR-63

HUMAN PERFORMANCE CENTER

DEPARTMENT OF PSYCHOLOGY

The University of Michigan, Ann Arbor

(6)

Intersession Variability and Stress: A Monte Carlo Study

(10) ELLIOT/NOMA

(15) N00014-76-C-0648

(12) 28p.

(9) Technical Report, No. 63

(11) June 1979

402 524

LB

THE HUMAN PERFORMANCE CENTER

DEPARTMENT OF PSYCHOLOGY

The Human Performance Center is a federation of research programs whose emphasis is on man as a processor of information. Topics under study include perception, attention, verbal learning and behavior, short- and long-term memory, choice and decision processes, and learning and performance in simple and complex skills. The integrating concept is the quantitative description, and theory, of man's performance capabilities and limitations and the ways in which these may be modified by learning, by instruction, and by task design.

The Center issues two series of reports. A Technical Report series includes original reports of experimental or theoretical studies, and integrative reviews of the scientific literature. A Memorandum Report series includes printed versions of papers presented orally at scientific or professional meetings or symposia, methodological notes and documentary materials, apparatus notes, and exploratory studies.

THE UNIVERSITY OF MICHIGAN

COLLEGE OF LITERATURE, SCIENCE AND THE ARTS

DEPARTMENT OF PSYCHOLOGY

INTERSESSION VARIABILITY AND STRESS: A MONTE CARLO STUDY

Elliot Noma

HUMAN PERFORMANCE CENTER TECHNICAL REPORT NO. 63

June, 1979

This research was supported by the Office of Naval Research, Department of Defense, under Contract No. N0014-76-0648 with the Human Performance Center, Department of Psychology, University of Michigan. The author was supported by a training grant from NIGMS (GM-01231) to the University of Michigan

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER: 014523-6-T
2. GOVT ACCESSION NO.:
3. RECIPIENT'S CATALOG NUMBER:
4. TITLE (and Subtitle): Intersession variability and stress: A Monte Carlo Study
5. TYPE OF REPORT & PERIOD COVERED: Technical
6. PERFORMING ORG. REPORT NUMBER: Technical Report No. 63
7. AUTHOR(s): Elliot Noma
8. CONTRACT OR GRANT NUMBER(s): N0014-76-C-0648
9. PERFORMING ORGANIZATION NAME AND ADDRESS: Human Performance Center, University of Michigan, Ann Arbor, MI 48104
10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS: NR 197-035
11. CONTROLLING OFFICE NAME AND ADDRESS: Engineering Psychology Program, Office of Naval Research; 800 N. Quincy Street, Arlington, VA 22217
12. REPORT DATE: June 1979
13. NUMBER OF PAGES: 19
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office):
15. SECURITY CLASS. (of this report): Unclassified
15a. DECLASSIFICATION/DOWNGRADING SCHEDULE:
16. DISTRIBUTION STATEMENT (of this Report): ~~Qualified requests may obtain copies of this report from DDC. Others may obtain copies of this report from Office of Technical Services, Department of Commerce~~.

DISTRIBUTION STATEMENT A
Approved for public release;
Distribution Unlimited

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report):
18. SUPPLEMENTARY NOTES:
19. KEY WORDS (Continue on reverse side if necessary and identify by block number):
multidimensional scaling
goodness-of-fit measures
Monte Carlo study
intersession variability

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Two Monte Carlo studies explore the relation of the tau measure of intersession response variability and the stress of the corresponding multidimensional scaling solution, thereby providing a statistical basis for evaluating the goodness-of-fit of a spatial configuration. In the first Monte Carlo study, the stress and tau of 10-, 16-, and 30-point configurations in 1, 2, 3, and 4 dimensions are shown to be linear functions of the internal error level. In the second study, these relations are shown to be relatively invariant with respect to the particular configurations. Three methods are

over

20. (cont'd)

proposed for establishing acceptable levels of stress for heuristic and for constrained multidimensional scaling.

Intersession variability and stress:
A Monte Carlo study[1]

Elliot Noma

The University of Michigan

April, 1979

Abstract

Two Monte Carlo studies explore the relation of the tau measure of inter-session response variability and the stress of the corresponding multidimensional scaling solution, thereby providing a statistical basis for evaluating the goodness-of-fit of a spatial configuration. In the first Monte Carlo study, the stress and tau of 10-, 16-, and 30-point configurations in 1, 2, 3, and 4 dimensions are shown to be linear functions of the internal error level. In the second study, these relations are shown to be relatively invariant with respect to the particular configurations. Three methods are proposed for establishing acceptable levels of stress for heuristic and for constrained multidimensional scaling.

Statistical guidelines for evaluating stress are essential for the successful application of multidimensional scaling. For this reason, Monte Carlo studies have been published establishing correspondences between internal error levels and stress values (Young, 1970; Sherman, 1972; Spence & Graef, 1974; Cohen & Jones, 1974). Unfortunately, all previous investigations have shortcomings (see Arabie, 1973): 1) inflated stress values due to local-minimum problems, 2) scaling of interpoint distances plus noise or random rank order dissimilarities does not guarantee recovery of the interpretation of the original configuration, 3) currently there is no way to independently estimate the error level to the distribution of stresses, and 4) all previous Monte Carlo studies concentrate only on local-minimum solutions, but scaling with constraints (Noma & Johnson, 1977) often produces suboptimal-stress solutions. In this paper a method around these complications is proposed.

In section 2, it is argued that the latent configuration is best assumed equivalent to the scaled configuration. This assumption avoids both inflated stresses due to recovery of suboptimal solutions and the recovery of non-representative solutions. The Monte Carlo methodology relating error to stress and error to intersession variability is introduced in section 3. In section 4, the results of two Monte Carlo studies are presented. Ways of applying intersession variability to evaluate stress appear in section 5.

2. The Latent Configuration

The multidimensional scaling methodology has been applied in two ways: 1) heuristic standard multidimensional scaling searches for structures in the data; 2) constrained multidimensional scaling with constraints emphasizes hypothesis testing. When multidimensional scaling is used as a heuristic tool, it is customarily assumed that the algorithm constructs a configuration that approximates a latent or "true" configuration. Also, only one scaled configuration is of

interest: the local-minimum solution. Scaling with constraints, however, produces configurations that are often suboptimal in terms of stress level. In addition, from a single dissimilarity set, many different configurations are produced by varying the constraints placed on interpoint distances (Borg & Lingoes, 1978), point coordinates (Bentler & Weeks, 1978; Bloxom, 1978), or order of point coordinates (Noma & Johnson, 1977). Each configuration may also have a stress comparable to that of the local-minimum solution yet illuminate a different structure in the data. This means that potentially many configurations could be representative of structure in the data. Since any one of these configurations, or none of them, may be the latent configuration, the latent configuration is best defined as the configuration produced by the scaling algorithm. This simplifying assumption also allows the separation of the recovery of the original structure and the production of the lowest attainable stress level. That is, by dictating that the structure is perfectly recovered, the stress may be examined alone. Also there is no possibility of suboptimal stress for a given dissimilarity set.

3. Methodology

By equating the latent and scaled configurations, the question is, given a configuration (C), how much noise must be added to the interpoint distances (D) to produce a given stress (S_1). That is, a matrix of interpoint distances plus noise (denoted by D_Σ) is computed for a given configuration. The matrix and the given configuration are input to a scaling program which computes a stesss value after zero iterations.

To generate the distance plus noise matrix the procedure described by Sherman (1972; Hefner, 1958; Ramsay, 1969) is used. Briefly, the procedure may be summarized as follows: 1) After specifying the number ofpoints (N) and dimensionality (d), a configuration is randomly generated in a d-dimensional

unit hypercube. 2) A number called the level of noise is computed by multiplying a specified error level (E), times the variance of the N*d coordinates (σ_c^2). 3) The elements of the dissimilarity matrix are generated by adding noise to the Euclidean distance between all N(N-1)/2 pairs of points:

$$d_{ij} = \sum_{k=1}^{k} (x_{ik} - x_{jk} + \varepsilon_{ijk})^2$$

where ε_{ijk} is a random variable distributed as $N(0, 2\sigma_c^2 E^2)$. 4) From these dissimilarities, the stress of the latent configuration is computed:

$$S_1 = f(C, D_\Sigma)$$

For a given number of points, dimensionality, and configuration, many simulated dissimilarity sets at a given error level will map out a distribution of stress values.

One measure of noise in the data to be scaled is the intersession variability. Due to the assumed ordinal nature of the input to the multidimensional scaling algorithm, the tau statistic (Kendall, 1962) is used as the measure of the correlation between dissimilarity sets from one session to another. By averaging taus from all pairs of dissimilarity sets one can derive the expected error level. For instance, intersession taus near unity imply that the error level is low so only configurations with near-zero stresses are acceptable. Configurations with stresses outside acceptable error bounds are considered inadequate representations of the data.

4. Results

Two Monte Carlo studies were done. The first characterizes the relationship of error level to mean stress and mean tau for specific configurations. The second determines the sensitivity of the error-stress and error-tau relationships

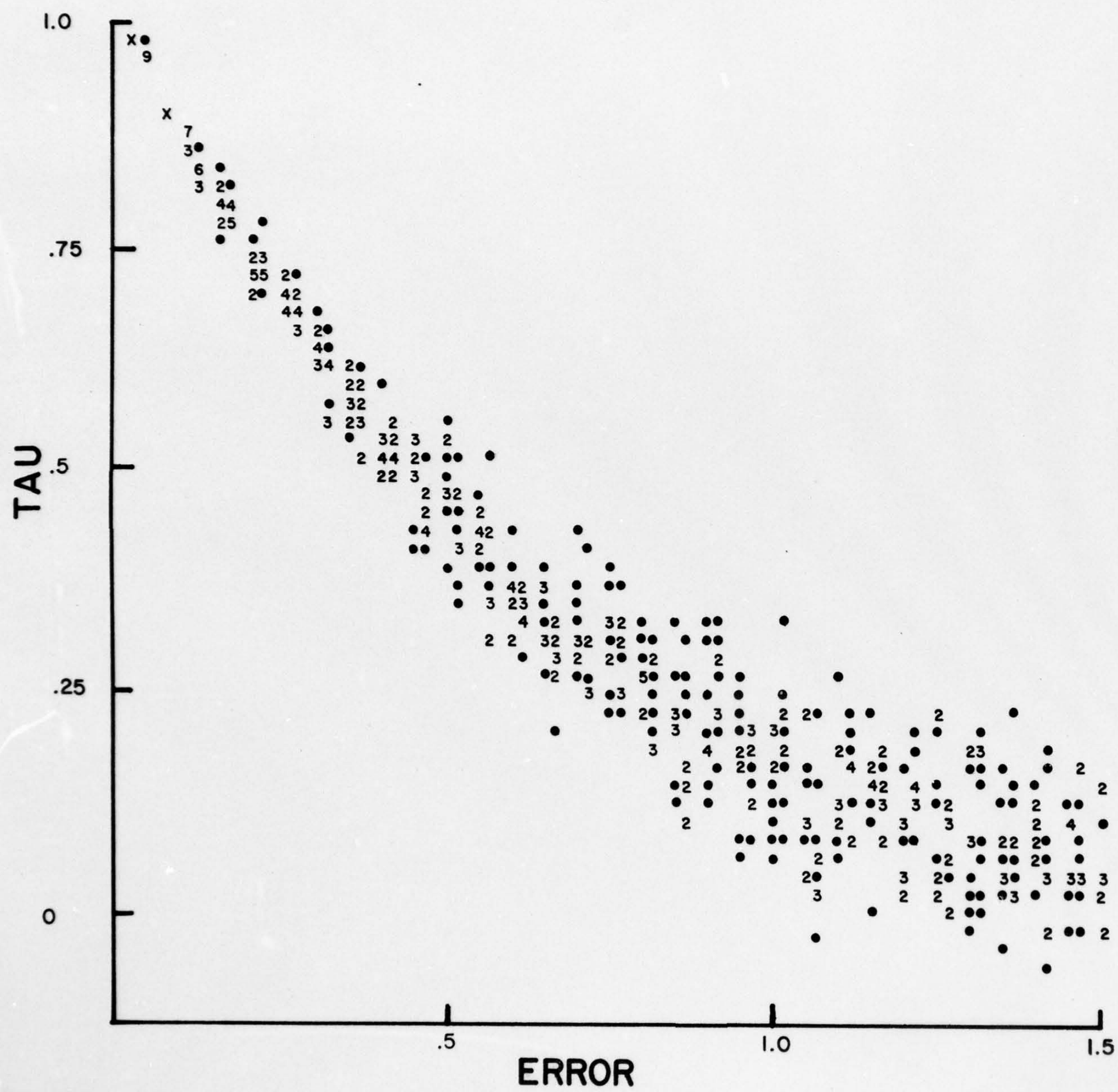
to different configurations.

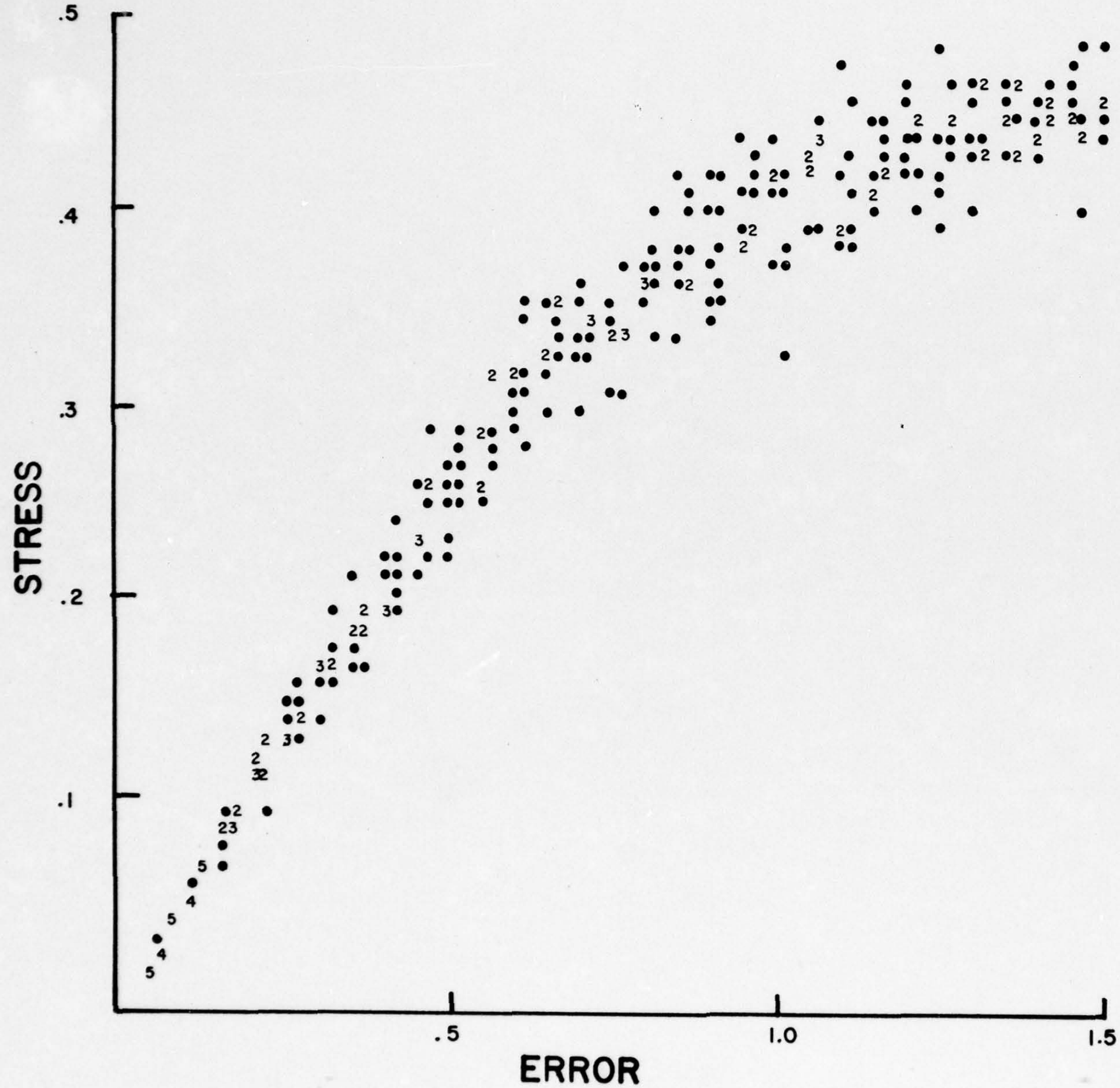
In the first, arbitrary configurations were chosen with 10, 16, and 30 points in 1, 2, 3, and 4 dimensions. For each of the 12 configurations, five dissimilarity sets were generated at error levels increasing from E = .025 by steps of .025. Figures 1 and 2 show typical error-tau and error-stress relationships from E = .025 to E = 1.5. Note that the functions are nearly linear up to about E = .750 before reaching asymptotes at stress = 45% and tau = 0. These relationships seem to typify all curves produced since all regressions using E values in the range .025 to .500 had correlations in excess of .94. Since scaling solutions would be excluded from further analysis with stress over 45% or intersession tau near 0, all further analysis was done for error levels from .025 to .5.

Figures 1 and 2 about here

The second Monte Carlo study explores the relation of the slopes of the error-stress and error-tau functions to the number of points, dimensionality, and specific configurations. Fifty dissimilarity sets were generated at each combination of 5 different random configurations at N=10, 16, 30, d=1, 2, 3, and 3 error levels (the error levels were picked to produce mean taus of approximately .5, .75, and .9 as predicted by the regression coefficients obtained in the first Monte Carlo study). For each of the 135 configurations, (5 x 3 x 3 x 3), means and variances of the stress distributions were computed for the set of 50 dissimilarities. To save computation, taus were computed only between the first 15 of the 50 dissimilarity sets. Means and variances of these 105 values, (15(15 - 1)/2), were computed for each configuration.

In accordance with the results of the first Monte Carlo study, for each


TAU
1.0
.75
.5
.25
0
.5
1.0
1.5
ERROR


STRESS
ERROR
.5
.4
.3
.2
.1
.5
1.0
1.5

fixed level of N and d, the error-mean stress and error-mean tau correlations were all in excess of .98. However, the 27 analyses of variance of the stress distributions across the five configurations for a given N, d, and error level were all significant at $p < 05$. Therefore it must be concluded that the two functions, the one relating error and mean stress and the one relating error and mean tau, are only relatively invariant with respect to specific configurations. Two other issues are of interest: the mean tau-to-mean stress relation and the variance of the taus and stresses for a given level of tau and stress. To estimate the slope of the tau-stress function, $\frac{\mu_{Stress}}{1-\mu_{tau}}$ was computed for each of the 135 configurations. Figure 3 shows the geometric means of these values for all combinations of N and d. The log ($\frac{\mu_{Stress}}{1-\mu_{tau}}$) values are then regressed on log (N) and log (d) yielding the following equation:

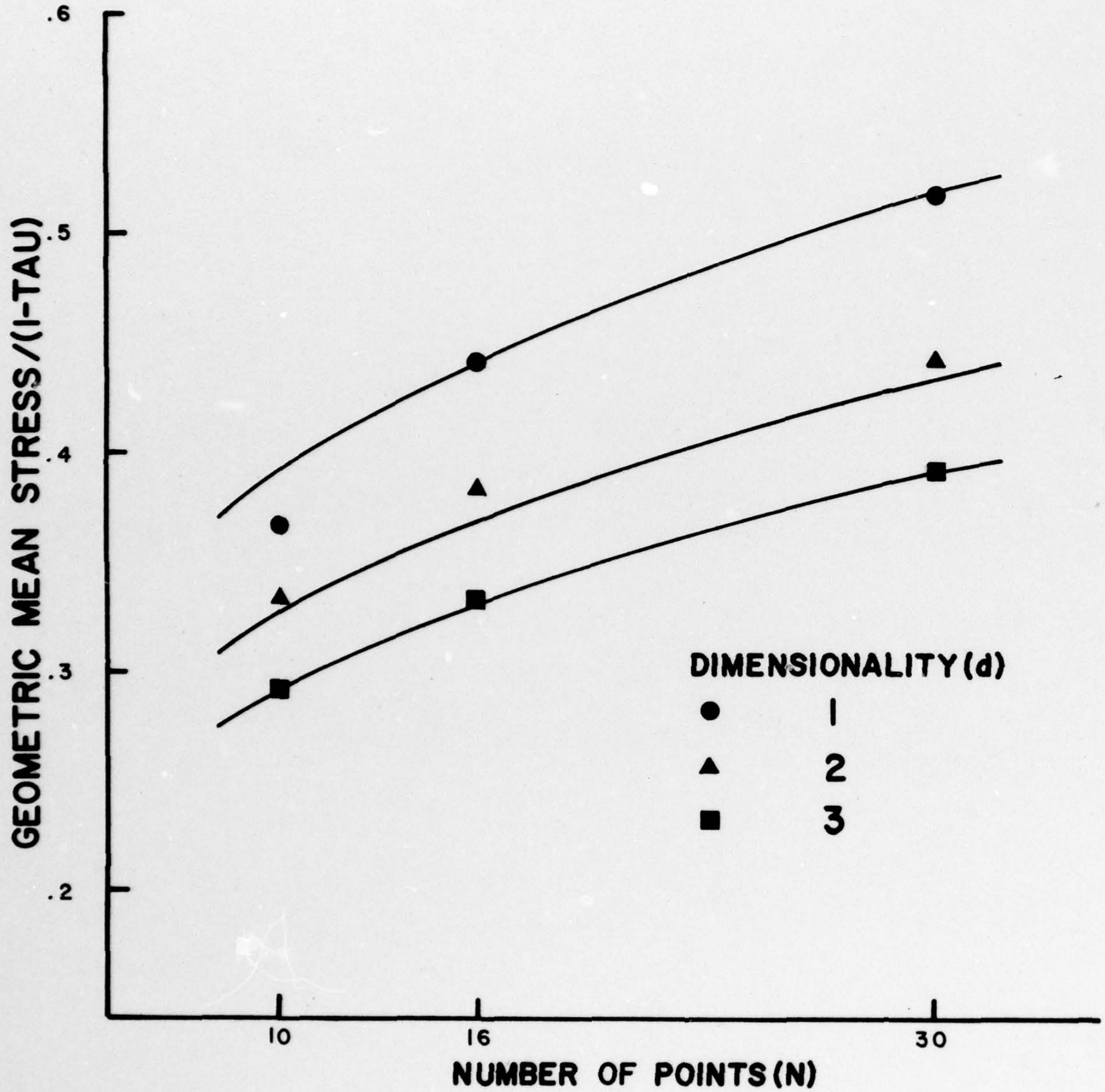
$$(1) \qquad \frac{\mu_{Stress}}{1-\mu_{tau}} = e^{-1.5301} N^{.25377} d^{-.25498} \quad r = .729$$

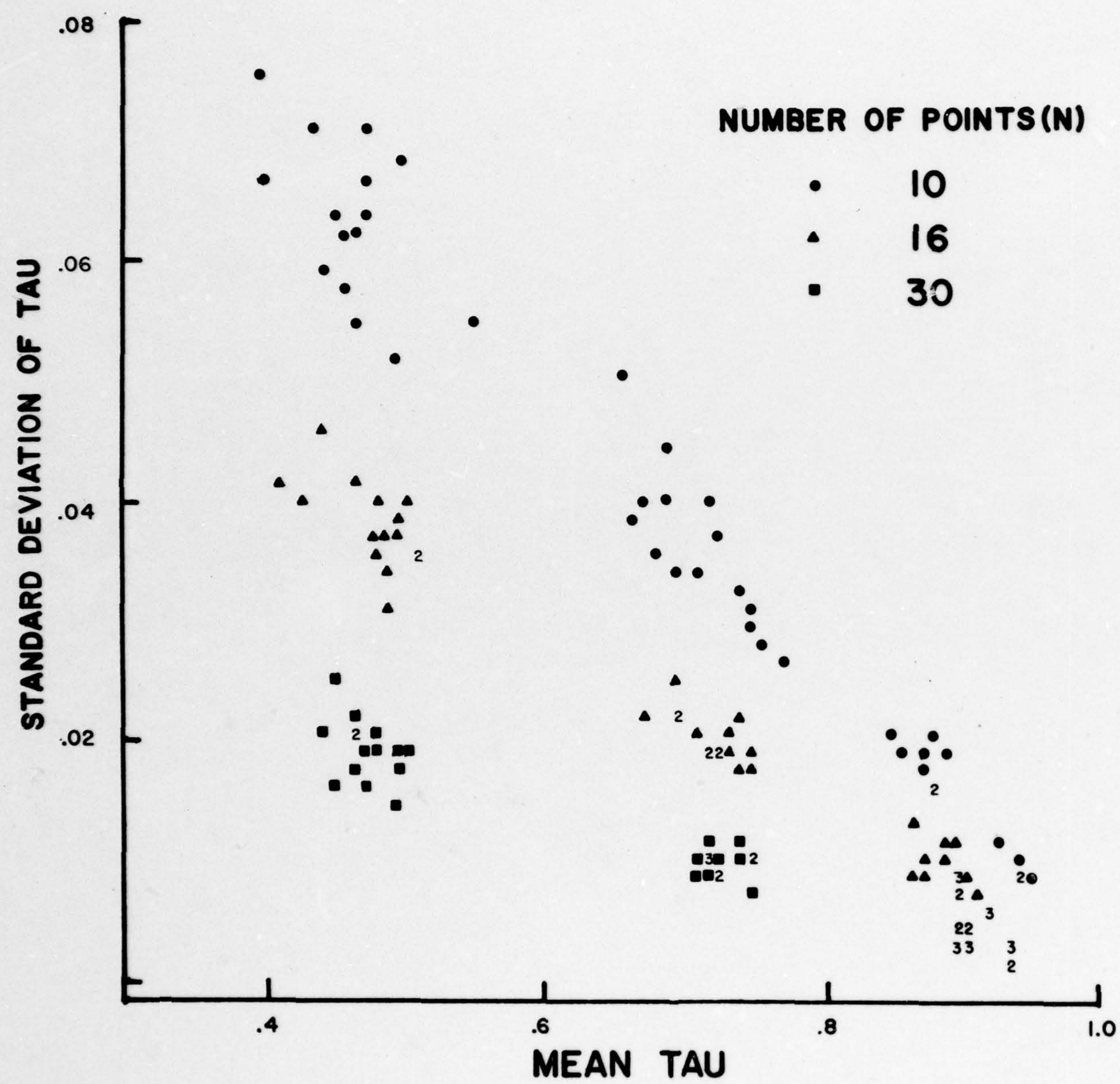
Similarly, the standard deviation-to-mean ratios of tau and stress (see Figures 4 and 5) were computed as these equations:

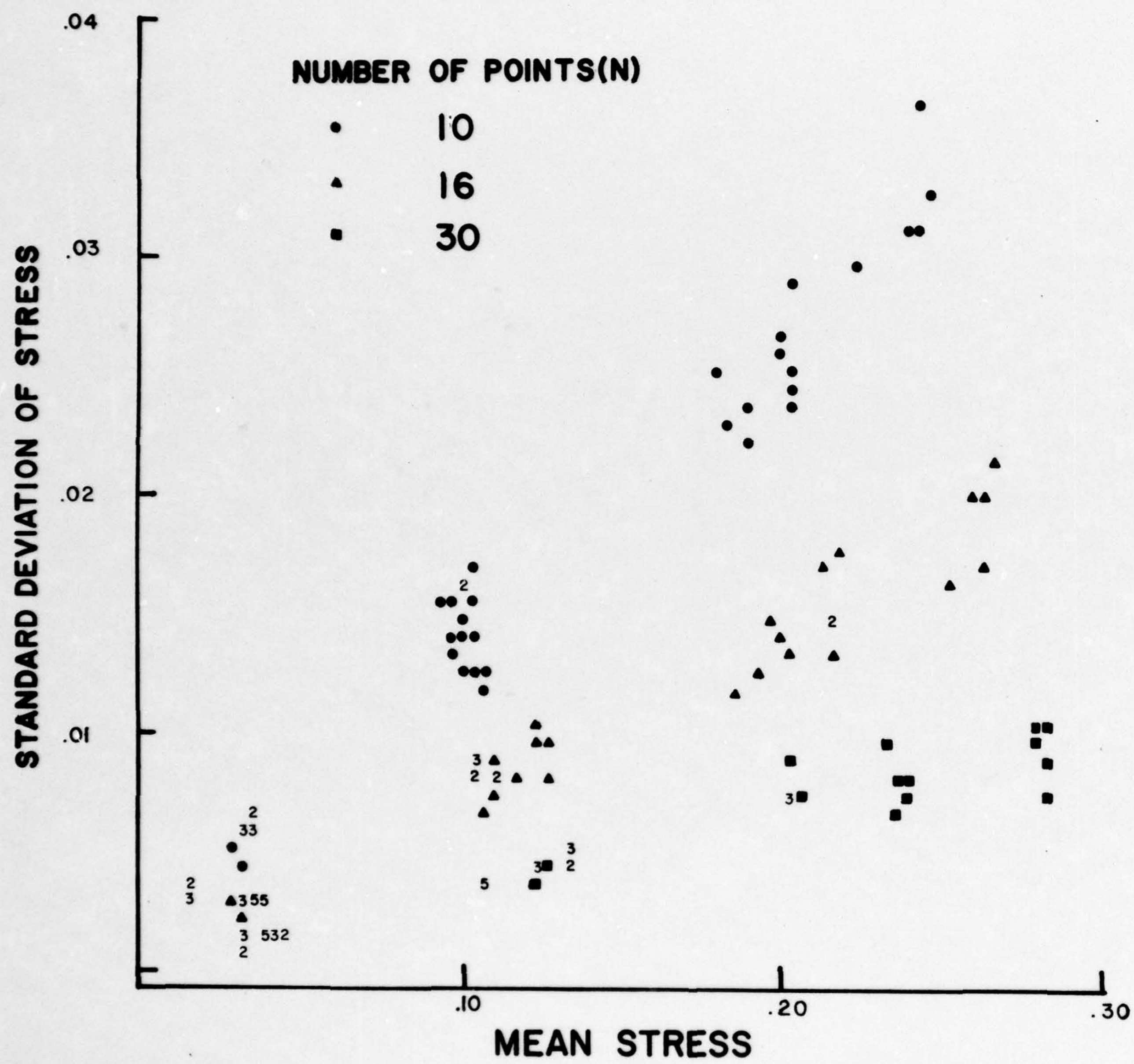
$$(2) \qquad \frac{\sigma_{tau}}{1-\mu_{tau}} = e^{.66718} N^{-1.1713} \qquad r = .970$$

$$(3) \qquad \frac{\sigma_{Stress}}{\mu_{Stress}} = e^{1.1278} N^{-1.3123} \qquad r = .964$$

Figures 3, 4, and 5 about here


GEOMETRIC MEAN STRESS/(1-TAU)
.6
.5
.4
.3
.2
10
16
30
NUMBER OF POINTS (N)
DIMENSIONALITY (d)
1
2
3


NUMBER OF POINTS (N)
10
16
30
STANDARD DEVIATION OF TAU
.08
.06
.04
.02
MEAN TAU
.4
.6
.8
1.0



NUMBER OF POINTS(N)
10
16
30
STANDARD DEVIATION OF STRESS
.04
.03
.02
.01
.10
.20
.30
MEAN STRESS

5. Discussion

Previous techniques for statistically evaluating stress are inadequate for a variety of reasons. Fixed criteria (Kruskal, 1964) are affected by the number of points and the dimensionality. "Looking for the elbow" requires the existence of such an elbow. Other Monte Carlo studies have the shortcomings of inflated stresses due to local-minimum problems (Arabie, 1973; Spence, 1974). Evaluating the output of constrained multidimensional scaling programs is even more difficult since the scaled configurations are usually not a local-minimum solution. Therefore all previous Monte Carlo studies are inappropriate since they deal only with local-minimum solutions. Attempts to extend the Monte Carlo results by counting the number and type of constraints also appear inadequate (see Noma & Johnson, 1977). In this section, three different methods are proposed for establishing acceptable bounds on stress in heuristic multidimensional scaling. The first two are also applicable to constrained multidimensional scaling.

All three methods are based on comparisons of mean stress and mean tau. To compute mean stress ($\overline{S}_1$), a single configuration (C') is produced using some average of responses over replications in a two-way analysis or a group space from a three-way analysis (e.g. INDSCAL - Carroll & Wish, 1974). The stresses are then computed for each of the r replications with the same configuration:

$$S_{1i} = f(C', D_i) \qquad i = 1,\ldots,r$$

and the mean stress is computed. Mean tau ($\overline{\tau}$) is computed by averaging the taus for all pairs of replications:

$$\tau_{ij} = (D_i, D_j) \qquad i = 1, \ldots, r \qquad j = 1,\ldots,r \qquad i \neq j$$

In method one, the tau predicts the mean stress ($\overline{S}_1$) using either equation 1 or the appropriate ratio of $\frac{\mu_{\text{Stress}}}{1-\mu_{\text{tau}}}$ in Figure 3. The empirical mean stress

($\bar{S}_1$) must fall within specified confidence bounds of $\hat{S}$ for the configuration to be acceptable.

In method two, varying amounts of error are added to the interpoint distances (D_Σ) of the scaled configuration (C') to determine an error stress curve. Assuming this curve is linear within a reasonable range of error values, the error value ($\hat{E}$) for the empirical stress ($\bar{S}_1$) is derived from the regression equation. The range of compatible taus is then easily computed using the formula (see Figure 6):

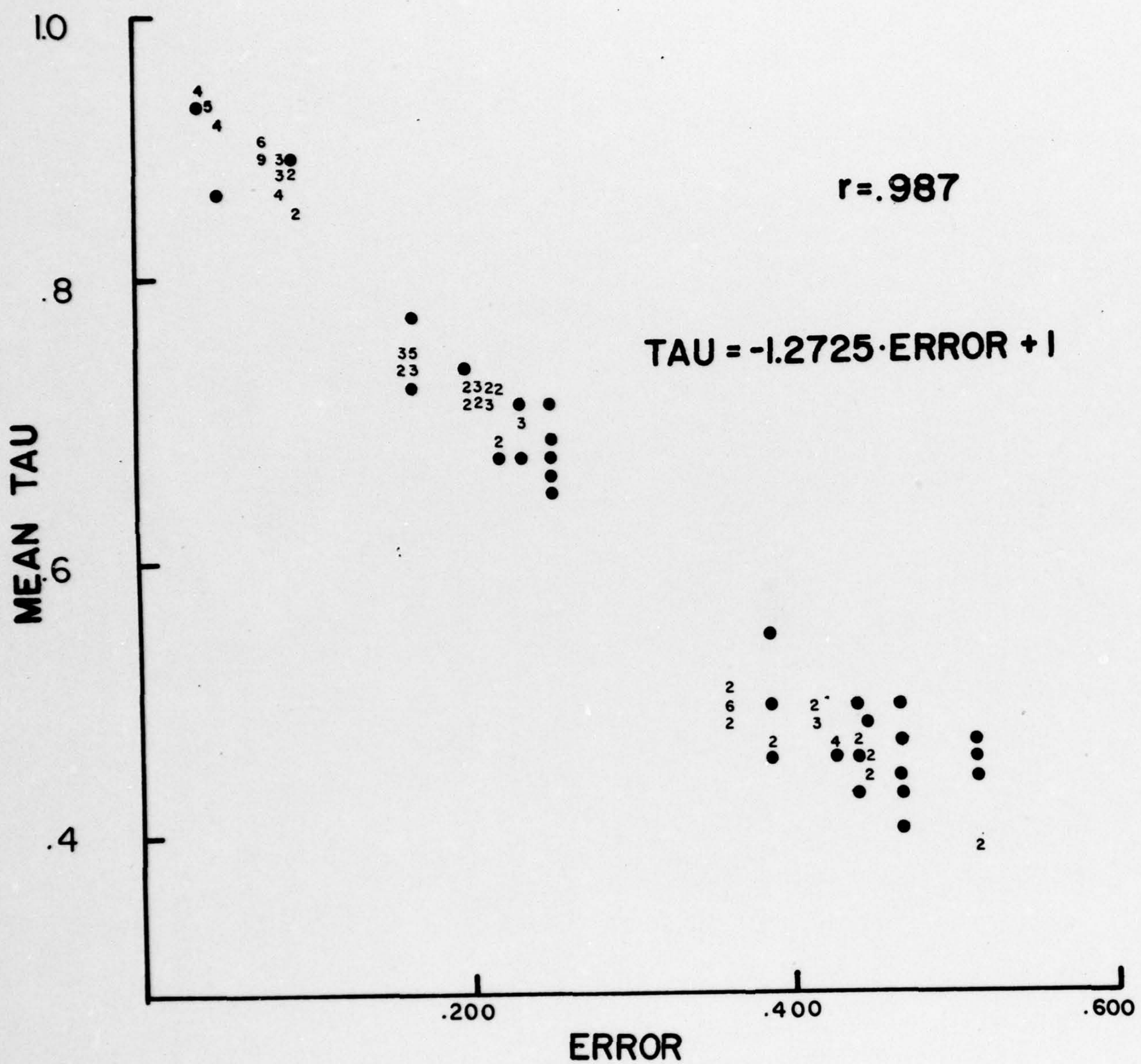
$$\hat{\tau} = -1.2725\ \hat{E} + 1 \qquad\qquad r = .987$$

and the variance of τ is found by using equation (2).

Figure 6 about here

The third method can be applied only to scaled local-minimum solutions. In contrast to the first two methods, no assumptions are made as to the relationship between the latent and the scaled configurations. One only assumes that a latent configuration exists. Previous Monte Carlo studies (e.g. Sherman, 1972) are first used to estimate the error level ($\hat{E}$) given the mean stress ($\bar{S}_1$). This error level is then used, as in method two, to determine a range of acceptable taus.

In all three methods, stresses that are too high indicate an inadequate configuration. In this case, an attempt should be made to scale the configuration in a higher dimensional space. Stresses that are too low indicate a fit that is too good and the scaling should be done in a lower dimensional space or with constraints.


r=.987
TAU = -1.2725·ERROR + 1
MEAN TAU
1.0
.8
.6
.4
ERROR
.200
.400
.600

References

Arabie, P. Concerning Monte Carlo evaluations of nonmetric multidimensional scaling algorithms. _Psychometrika_, 1973, _38_, 607-608.

Bentler, P. M. & Weeks, D. G. Restricted multidimensional scaling models. _Journal of Mathematical Psychology_, 1978, _17_, 138-151.

Bloxom, B. Constrained multidimensional scaling in N space. _Psychometrika_, 1978, _43_, 397-408.

Borg, I. & Lingoes, J. C. Nonmetric multidimensional scaling with order constraint on the distances. Michigan Mathematical Psychology Program technical report. (MMPP) 1978-3.

Carroll, J. D. & Wish, M. Models and methods for three-way multidimensional scaling. In D. H. Krantz, R. C. Atkinson, R. D. Luce, and P. Suppes (Eds.), _Contemporary Developments in Mathematical Psychology_, Vol. II: Measurement, Psychophysics, and Neural Information Processing. San Francisco: Freeman, 1974, pp. 57-105.

Cohen, H. S. & Jones, L. E. The effects of random error and subsampling of dimensions on recovery of configurations by non-metric multidimensional scaling. _Psychometrika_, 1974, _39_, 69-90.

Hefner, R. Extensions of the law of comparative judgment to discriminable and multidimensional stimuli. Unpublished doctoral dissertation, University of Michigan, Ann Arbor, Michigan, 1958.

Kendall, M. G. _Rank Correlation Methods_. London: Griffin, 1962.

Kruskal, J. B. Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis. _Psychometrika_, 1964, _29_, 1-27.

Noma, E. & Johnson, J. Constraining nonmetric multidimensional scaling configura-

tions. Human Performance Center Technical Report No. 60 (014523), University of Michigan, August, 1977.

Ramsay, J. O. Some statistical considerations in multidimensional scaling. Psychometrika, 1969, 34, 167-182.

Sherman, C. R. Nonmetric multidimensional scaling: A Monte Carlo study of the basic parameters. Psychometrika, 1972, 37, 323-355.

Spence, I., and Graef. On random rankings studies in nonmetric scaling. Psychometrika, 1974, 39, 267-268.

Young, F. W. Nonmetric multidimensional scaling: Recovery of metric information. Psychometrika, 1970, 35, 455-473.

Footnote

[1]This research was supported by the Office of Naval Research, Department of Defense, under Contract No. N0014-76-0648 with the Human Performance Center, Department of Psychology, University of Michigan. The author was supported by a training grant from NIGMS (GM-01231) to the University of Michigan.

Figure Captions

1. Simulated taus for an arbitrary 16 point configuration in two dimensions.
2. Simulated stresses for an arbitrary 16 point configuration in two dimensions.
3. Mean slope of the stress-tau relationship for the mean stress and tau values of the 135 random configurations. Lines describe the best fitting log-linear function of N and d (see text).
4. The standard deviation of the tau distribution as a function of the mean tau of the 135 random configurations.
5. The standard deviation of the stress distribution as a function of the mean stress of the 135 random configurations.
6. Mean tau as a function of the error level for the 135 random configurations.

OFFICE OF NAVAL RESEARCH

Code 455

TECHNICAL REPORTS DISTRIBUTION LIST

OSD

CDR Paul R. Chatelier
Military Assistant for Training
and Personnel Technology
Office of the Deputy Under Secretary
of Defense
OUSDRE (E&LS)
Pentagon, Room 3D129
Washington, DC 20301

Department of the Navy

Director
Engineering Psychology Programs
Code 455
Office of Naval Research
800 North Quincy Street
Arlington, Virginia 22217 (5 cps)

Director
Operations Research Programs
Code 434
Office of Naval Research
800 North Quincy Street
Arlington, Virginia 22217

Director
Statistics and Probability Program
Code 436
Office of Naval Research
800 North Quincy Street
Arlington, Virginia 22217

Director
Physiology Program
Code 441
Office of Naval Research
800 North Quincy Street
Arlington, Virginia 22217

Commanding Officer
ONR Branch Office
ATTN: Dr. J. Lester
Building 114, Section D
666 Summer Street
Boston, MA 02210

Commanding Officer
ONR Branch Office
ATTN: Dr. C. Davis
536 South Clark Street
Chicago, IL 60605

Commanding Officer
ONR Branch Office
ATTN: Dr. E. Gloye
1030 East Green Street
Pasadena, CA 91106

Office of Naval Research
Scientific Liaison Group
American Embassy, Room A-407
APO San Francisco, CA 96503

Director
Naval Research Laboratory
Technical Information Division
Code 2627
Washington, DC 20375 (6 cps)

Dr. Robert G. Smith
Office of the Chief of Naval
Operations, OP987H
Personnel Logistics Plans
Washington, DC 20350

Department of the Navy

Naval Training Equipment Center
ATTN: Technical Library
Orlando, FL 32813

Human Factors Department
Code N215
Naval Training Equipment Center
Orlando, FL 32813

Dr. Alfred F. Smode
Training Analysis and Evaluation Group
Naval Training Equipment Center
Code N-00T
Orlando, FL 32813

Dr. Gary Poock
Operations Research Department
Naval Postgraduate School
Monterey, CA 93940

Dean of Research Administration
Naval Postgraduate School
Monterey, CA 93940

Mr. Warren Lewis
Human Engineering Branch
Code 8231
Naval Ocean Systems Center
San Diego, CA 92152

Dr. A. L. Slafkosky
Scientific Advisor
Commandant of the Marine Corps
Code RD-1
Washington, DC 20380

Mr. Arnold Rubinstein
Naval Material Command
NAVMAT 98T24
Washington, DC 20360

Commander
Naval Air Systems Command
Human Factors Programs
NAVAIR 340F
Washington, DC 20361

Commander
Naval Air Systems Command
Crew Station Design,
NAVAIR 5313
Washington, DC 20361

Dr. James Curtin
Naval Sea Systems Command
Personnel & Training Analyses Office
NAVSEA 074C1
Washington, DC 20362

Commander
Naval Electronics Systems Command
Human Factors Engineering Branch
Code 4701
Washington, DC 20360

Bureau of Naval Personnel
Special Assistant for Research Liaison
PERS-OR
Washington, DC 20370

CDR R. Gibson
Bureau of Medicine and Surgery
Aerospace Psychology Branch
Code 513
Washington, DC 20372

LCDR Robert Biersner
Naval Medical R&D Command
Code 44
Naval Medical Center
Bethesda, MD 20014

Department of the Navy

Dr. Arthur Bachrach
Behavioral Sciences Department
Naval Medical Research Institute
Bethesda, MD 20014

LCDR T. Berghage
Naval Medical Research Institute
Behavioral Sciences Department
Bethesda, MD 20014

Dr. George Moeller
Human Factors Engineering Branch
Submarine Medical Research Lab
Naval Submarine Base
Groton, CT 06340

Chief
Aerospace Psychology Division
Naval Aerospace Medical Institute
Pensacola, FL 32512

Dr. Fred Muckler
Navy Personnel Research and
Development Center
Manned Systems Design, Code 311
San Diego, CA 92152

Navy Personnel Research and
Development Center
Management Support Department
Code 210
San Diego, CA 92152

Navy Personnel Research and
Development Center
Code 305
San Diego, CA 92152

CDR P. M. Curran
Human Factors Engineering Division
Naval Air Development Center
Warminster, PA 18974

Department of the Army

Mr. J. Barber
HQS, Department of the Army
DAPE-PBR
Washington, DC 20546

Dr. Joseph Zeidner
Technical Director
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Director, Organizations and Systems
Research Laboratory
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Technical Director
U.S. Army Human Engineering Labs
Aberdeen Proving Ground, MD 21005

Department of the Air Force

U.S. Air Force Office of
Scientific Research
Life Sciences Directorate, NL
Bolling Air Force Base
Washington, DC 20332

Air University Library
Maxwell Air Force Base, AL 36112

Other Government Agencies

Defense Documentation Center
Cameron Station, Bldg. 5
Alexandria, VA 22314 (12 cps)

Other Government Agencies

Dr. Stephen J. Andriole
Director, Cybernetics Technology Office
Defense Advanced Research Projects Agency
1400 Wilson Blvd.
Arlington, VA 22209

Dr. Stanley Deutsch
Office of Life Sciences
National Aeronautics and
Space Administration
500 Independence Avenue
Washington, DC 20546

Other Organizations

Dr. James H. Howard
Department of Psychology
Catholic University
Washington, DC 20064

Journal Supplement Abstract Service
American Psychological Association
1200 17th Street, N. W.
Washington, DC 20036 (3 cps)

Dr. J. A. Swets
Bolt, Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Dr. Robert Williges
Human Factors Laboratory
Virginia Polytechnical Institute
and State University
130 Whittemore Hall
Blacksburg, VA 24061

Foreign Addressees

Director, Human Factors Wing
Defence and Civil Institute
of Environmental Medicine
P. O. Box 2000
Downsville, Toronto, Ontario
CANADA